TIME-FREQUENCY METHODS IN A STUDY OF VOLUNTARY MOVEMENTS

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Abstract - **Two methods operating in time-frequency space were applied to analysis of brain activity accompanying voluntary finger movements. The first one, based on Matching Pursuit approach, provided high-resolution distributions of power in time-frequency space. The second method called short time Directed Transfer Function (SDTF), based on a multichannel autoregressive model (MVAR), allowed for investigation of EEG activity propagation as a function of time and frequency. The evidence of "cross-talk" between different areas of sensorimotor cortex was found.**

Keywords: non-stationaryEEG analysis; event related synchronization / desynchronization; Matching Pursuit; multichannel autoregressive model; short time Directed Transfer Function.

I. INTRODUCTION

One of the problems, which requires application of non-stationary signal analysis is understanding of EEG activity connected with movement planning. This problem has been in the center of interest during last few years, since its study opens the possibility of brain-computer interface design. It was found that the planning and the execution of voluntary movements are related to the pre-movement attenuation (event related desynchronisation –ERD) and post-movement increase in amplitude (event related synchronisation – ERS) of alpha and beta rhythms in certain areas of motor and sensory cortex. These phenomena were mainly investigated by means of spectral analysis and band-pass filtering [1]. We present application of two methods, tailored for analysis of non-stationary signals: high-resolution time-frequency analysis based on Matching Pursuit (MP), and estimation of propagation of EEG activity by short time Directed Transfer Function (SDTF) based on vector multichannel AR model (MVAR). Both methods are complementary since the first one takes into account amplitude distribution, and the second one also includes phase information; both operate in time-frequency domain.

II. METHODOLOGY

A. Experimental data

The experiment has been performed on three volunteers. EEG was registered from 24 electrodes placed over motor and sensory areas (partly over visual cortex). The signal was analogue bandpass filtered in the 0.5-100 Hz range and sampled at a 256 Hz frequency. The subject was lying in a dim room with his eyes open. Movements of index finger preformed approximately 5 seconds after a quiet sound generated every 10 to 14 seconds were detected by a microswitch.

B. Energy distribution in time-frequency estimated by MP

The Matching Pursuit (MP) algorithm relies on a decomposition of the signal into basic waveforms from a very large and redundant set of functions [2], [3]. In this paper, a new improved version of algorithm based on stochastic dictionaries [4] was used. It removes the bias introduced by dyadic sampling of the time and frequency plane present in the original algorithm [2]. In the framework of the MP approach, all signal structures are parameterized in terms of amplitude, time occurrence, time span, and frequency. This kind of representation allows for high-resolution estimation of the time-frequency distribution of signal power, free of cross-terms. We have applied the MP decomposition procedure to each trial and then we constructed averaged maps of power. ERS/ERD maps were calculated by dividing each spectral component by the signal power in the relevant frequency averaged in the epoch 4.5 s to 3.5 s before movement:

$$\mathrm{ERS/ERD} = \frac{P(f,t) - P_{\mathrm{ref}}(f)}{P_{\mathrm{ref}}(f)} \qquad (1)$$

where: $P(f, t)$ is the value of averaged power map in a given time-frequency point, $P_{\mathrm{ref}}(f)$ is an average power in reference time calculated for frequency f.

C. The SDTF method

A drawback of the DTF method [5], designed to determine propagation between channels, was a minimum required length of the data window on the order of seconds (increasing with the number of

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simultaneously analyzed channels). This requirement effectively limited the possibilities of the method since information processing in the brain involves shorter epochs. Recently, a new method of the estimation of the MVAR coefficients was developed [6], which made evaluation of AR model coefficients possible with short time epochs, when multiple repetitions were available. The first step in the estimation of model coefficients is calculation of the correlation matrix $\mathbf{R}(t)$. The conventional method of obtaining $\mathbf{R}(t)$ estimate is based on an assumption of ergodicity. In order to obtain statistically significant estimate the signal has to be long enough. However, having long stationary epochs in EEG analysis is an exception rather than a rule.

When many realizations of the same stochastic process are available, much shorter data window can be applied. The information from all the trials can be used to increase the statistical significance of the fitted model parameters. The correlation between channel i and channel j can be calculated for each realization and then averaged over all the realizations:

$$\tilde{R}_{ij}(s) = \frac{1}{N_T} \sum_{r=1}^{N_T} R_{ij}^{(r)}(s) = \\ = \frac{1}{N_T} \sum_{r=1}^{N_T} \frac{1}{n-|s|} \sum_{t=1}^{n-|s|} X_i^{(r)}(t) X_j^{(r)}(t-s) \qquad (2)$$

where $X_i(t)$ denotes data point in the i-th channel at the time t, $R_{ij}(s)$ are the elements of correlation matrix $\mathbf{R}(t)$ calculated for time lag t=s, n is the length of the data record, N_T is the number of the realizations, $R_{ij}^{(r)}(s)$ denotes the elements of $\mathbf{R}^{(r)}(s)$ — correlation matrix calculated for time lag t=s in the realization r.

From the correlation matrix given by eq. (2) the MVAR parameters and the transfer matrix $H_{ij}(f)$ can be calculated The transfer matrix $\mathbf{H}(f)$ is asymmetric and contains information about the phase and frequency dependencies between signals. The non-normalized DTF function (as well as SDTF), describing transmission from channel i to j at frequency f is defined as:

$$\theta_{ji}^2(f) = |H_{ji}(f)|^2 \qquad (3)$$

It was shown that DTF (or SDTF) function defined above is equivalent to Granger casuality measure [7]. Based on the calculations of the AIC criterion for individual epochs, a common model of order 5 was estimated for all the data windows. The analysis was performed for 8 second long artifact-free trials including 5 seconds before the finger movement onset, and 3 seconds after the movement. The trials were aligned with respect to the movement onset, forming a set of realizations of a stochastic process. An MVAR model was fitted to the 80-sample long window, using information from all the trials. The estimated MVAR model parameters were used to calculate the SDTF function. Then, the window was shifted by 10 samples, and the fitting procedure was applied to the new data window. By sliding the data window over the whole time range, time-frequency characteristics of SDTF were found. The bootstrap method was used to evaluate the error of the estimated SDTFs. The size of the pool of randomly selected trials was equal to the number of trials; they were different for each recording session (ranging from 55 to 57 trials). For each session the calculation was repeated 100 times.

III. RESULTS

The signals were decomposed into Gabor functions by iterative adaptive procedure and then the time-frequency maps of power and ERD/ERS were constructed (Fig.1). High resolution allowed for distinction of temporal behavior of two mu components; namely desynchronization of higher energy component started earlier and lasted longer, especially in locations close to sensorimotor hand area. Two mu components differed in energy among subjects, but they were usually separated by 2 Hz. The respective frequencies were found as maxima of binomial frequency distributions. The parametric description of waveforms in the framework of the MP approach makes construction of such histograms straightforward At the map showing ERD/ERS in in time-frequency coordinates several harmonics of mu and beta rhythms were observed, which increased and decreased together with the basic components.

The effect of mu desynchronization was best visible for electrodes C1 and C3 in the case of right hand movements, and electrodes C2 and C4 for left hand movements for all right handed subjects. For the left-handed subject, the lateralization was less pronounced. Beta band of EEG is broader than mu band and rhythmical components are harder to distinguish. One general feature can be noticed, namely for electrodes overlying motor and sensory areas of hand there is a predominance of lower frequencies from 15 to 20 Hz, with a peak at 18 Hz. For electrodes lying more centrally the spectral distribution of ERS in beta band (15-23 Hz) is mostly uniform.

From the time profile one could try to judge in what locations the ERS starts first. However, statistical fluctuations make this task rather difficult. The second method proposed by us — SDTF — is more reliable in this respect. The first striking feature of SDTF behavior is that from certain derivations activity is propagated in several directions, while some other derivations are “silent”. For electrodes lying over the somatosensory and motor area, there is a pronounced decrease of outflow around the time of movement onset. This is not

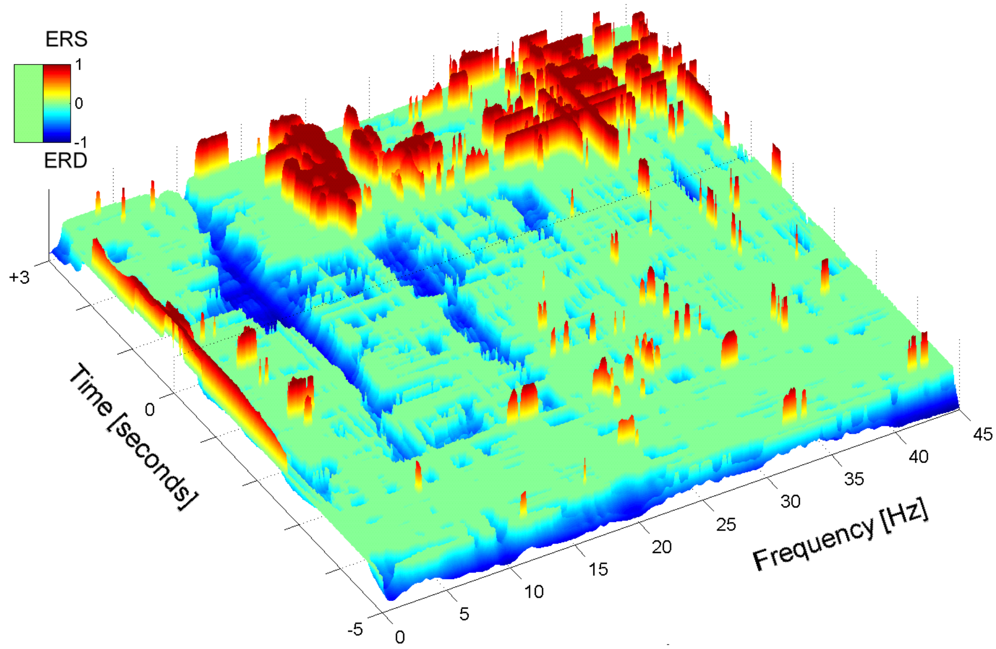

Fig. 1. Relative EEG power change in electrode C1 for right hand finger movement. (Movement onset in time 0, reference time -4.5 to -3.5 s.)

the case for electrodes P3, P1, Pz lying over visual cortex. During the whole investigated epoch the propagation from these electrodes can be observed. The outflows are directed not only to the neighboring electrodes in the posterior region of the head, but also to some central or even centro-frontal electrodes. The decrease of EEG activity propagation from electrodes lying in the cortex area associated with finger movement is accompanied with EEG propagation from electrodes located in the other areas, including areas of the sensory and motor cortex corresponding to the other parts of the body.

In order to see the pattern of the EEG propagation more clearly we have integrated SDTF function in certain frequency bands and certain time windows. Then we have calculated a "relative outflow" as a ratio of SDTF in the given frequency band during movement to the SDTF in the same frequency band at the reference epoch.

We can observe the increase of activity propagating from locations C5, Cz, and Pz. Electrode Cz corresponds to the somatosensory foot area and C5 to the facial area. The observed EEG flows can be interpreted as focal ERD/surround ERS effect [1].

The main directions of beta rhythm propagation are from Fc1, Fc3 and Cpz electrodes (illustrated in Fig. 3 for one of the subjects).

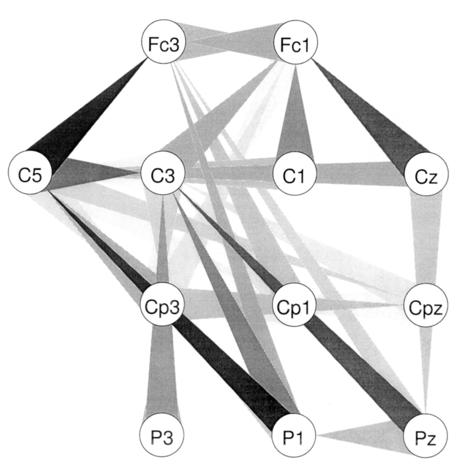

Fig. 2. The change in outflows in the 8-15 Hz frequency band before the movement (-2 to 0 s) in relation to the background activity (-5 to -3 s).

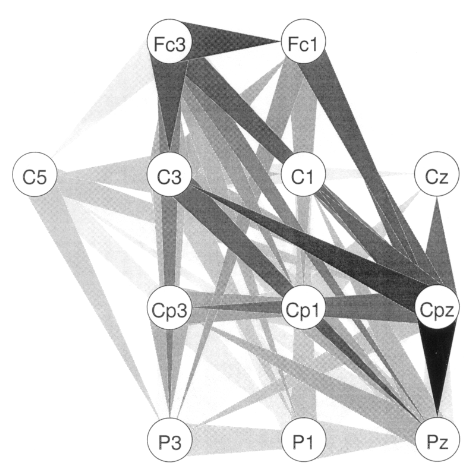

Fig. 3. Ratios of SDTF after movement (+1 to +2 s) to SDTF before movement (-5 to –3 s) in a frequency band 15-30 Hz.

IV. DISCUSSION

The results presented above demonstrate that both of the proposed methods not only clearly describe phenomena observed in earlier works, but they also bring new information. The separation of the two components in mu band is usually performed by filtering in the frequency bands 8-10 Hz and 10-12 Hz. However, such a fixed division may be misleading since upper and lower mu components differ for different subjects. Features of ERD/ERS, which were previously observed by means of different, especially tailored procedures, can be grasped by one glance at the time-frequency distribution of energy. Time-frequency representation can be obtained also by means of spectrograms, Cohen class distributions, continuous wavelet transform (WT). The drawback of Cohen class distributions is presence of cross-terms, which have to be eliminated by specially tailored procedures. Resolution of spectrograms is heavily limited by the length of the time window. Resolution of WT depends on frequency – for high frequencies it is poor in frequency and good in time and vice versa for low frequencies. MP is free of the above limitations. MP algorithm with stochastic dictionaries used in this work provides high and uniform resolution in time-frequency space.

Up to now, mainly amplitude properties of EEG during voluntary movements were considered. The SDTF function allows for the analysis of phase relationships between channels. The outflows of EEG activity before a movement onset confirm the hypothesis of focal ERD / surround ERS hypothesis. Additionally to the effect of increased activity in the foot area [1], we have also observed increased outflow of EEG activity from the facial area. The investigation of the time course of the beta activity outflow suggests the ways of communication between different parts of somatosensory cortex and motor cortex.

The strong propagation from frontal locations close to Fc3 and Fc1 is in agreement with the results of MEG measurements [8] indicating that beta activity probably has its origin in motor cortex areas, which are located more in front of somatosensory areas.

It is interesting to compare the results obtained by means of MP with those obtained by means of SDTF. The increase of beta outflows at second 1, from electrodes Fc3 and Cpz can also be observed at the time profiles in ERD/ERS maps obtained by MP. However, looking only at the time profiles it is not easy to judge which derivation is the primary source of activity. It is particularly the case for the derivation C3 — the impression that synchronization at this electrode starts before second one is confirmed by SDTF.

The strength of the SDTF estimate relies on truly multichannel treatment of EEG signals by MVAR model. The complicated mutual relationships between EEG signals coming from different brain structures can not be revealed by a pair-wise treatment, which can bring the misleading results e.g. in a case when two channels are fed from the same source. Our results support the hypothesis of "cross-talk" in beta band between the hand and leg motor areas, as well as other motor areas and they give an evidence of communication between motor and sensory areas

Both methods of the non-stationary signal analysis described in this paper are complementary - the MP based analysis gives very detailed information about amplitude distribution in a time-frequency domain, while SDTF has lower resolution in time-frequency, but it brings in the information about phase relationships between channels, making it possible to determine the propagation of EEG activity.

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